MODELLING AND SIMULATION OF ENERGY CONSUMPTION IN ELECTRIC VEHICLES AND ITS OPTIMIZATION

Synopsis

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1.0 INTRODUCTION

Energy Conservation is a global requirement for sustainable development of our planet. Since stone age, men have identified numerous sources of energy as per the growing need of the civilizations. Technology advancement has made it possible to convert energy from one form to the other and to transmit it from one place to another in an efficient way. In present times, energy consumption is one of the ways to estimate the development of a Nation. Human development Index has a positive correlation with energy consumption. Growing population, depletion of available natural resources and increasing pollution has compelled us to devise pollution free renewable energy sources at affordable prices. A revolution in the energy industry has come in recent years where renewable energy sources proved to be a promising alternative for the conventional energy sources.

In this context, electric vehicles (EV) have emerged as one of the promising solutions to curtail the immense usage of fossil fuels and to improve the quality of the environment at large. Since the last decade, advancements in battery technologies have made it possible to design EV as a dependable mode of intra city and inter city transportation. In recent years many automobile companies have launched their EV's in the market. These EV's are equipped with various features like State of Charge (SoC), available range estimators, fast charging mechanism, charging time indicator etc... The recent advancements in this area can be categorized as follows:

1.1 Battery Technology: A driving factor in EV development is the evolution in battery technology. Researchers and battery manufacturers continue to investigate and improve energy density, energy efficiency, battery life for improving the overall economics of battery. Solid-state batteries have emerged as the most promising solution with their potential to provide better energy density, safety, and control.

1.2 Driving Range: Longer driving range is both a challenge and a unique selling point of EV. Manufacturers are investing in battery technologies, aerodynamics, and vehicle design to extend the range of electric vehicles, making them more practical for mass consumers.

1.3 Charging Technology: The expansion and development of charging infrastructure is necessary for the general adoption of EVs. Cumulative efforts by Government and Business owners developed fast-charging networks and enhance charging convenience, including high-power chargers and

battery swapping strategies.

1.4 New Models for diverse customers: EV are in high demand across all segments of automobiles varying from city bus, truck, SUV's, sedan hatchback, scooters, bikes, and bicycles. Renowned automobile companies and new startup ventures are offering a wide range of EV's to customers as per their needs.

1.5 Autonomous Driving: Tesla has launched an EV with a feature of autonomous driving. Research and development in AI and sensor technologies are evolving to incorporate better autonomous driving capabilities in electric vehicles.

1.6 Vehicle to Grid (V2G) Technology: V2G technology allows two-way flow of electricity from Grid to EV and vice versa. EV can receive power from the grid for charging and can also send power back to it during idle period. The idea is to provide stability to the electricity grid during peak load hours and additional revenue opportunities for EV owners.

1.7 Regenerative Braking: Recently EV's incorporated regenerative braking system to improve the efficiency of EV by capturing and converting kinetic energy back into electrical energy during braking.

1.8 Internet Inside: EVs are becoming more connected, allowing for internet updates, remote monitoring, and interactive user experiences. E-Connectivity also facilitates features like smart charging and integration with smart home systems.

2.0 LITERATURE REVIEW

Lithium-ion (Li-ion) batteries are largely used as an energy source in electric vehicles (EVs) and hybrid electric vehicles (HEVs) [1], [2] because of high energy density and for their fast charging and low self-discharging rate [3]. Battery aging occurs over a period depending on its usage which results in power fading and capacity loss [4]. The factors responsible for battery aging are degradation of performance characteristics, cycle count, Depth of discharge (DoD) as batteries that are regularly deeply discharged (used until they are nearly empty) will age more quickly than those that are shallow cycled. Lithium-ion batteries are particularly sensitive to deep discharges [5], high temperatures can accelerate battery aging. Heat increases the rate of chemical reactions inside the battery, leading to faster degradation. Conversely, very low temperatures can reduce battery performance temporarily [6][7]. Charging rate (C-rate) is also

a principal stress factor which affects the aging of batteries. Charging and discharging batteries at high DoD, high temperatures, and high C-rate enhance the aging process, as well as results in unbalanced cells in a battery pack [7].

Proper analysis of Li-ion battery health is necessary to ensure safety while batteries are under operation in EV. The battery state-of-health (SoH) estimation and the remaining useful life (RUL) analysis are used to assess and examine its age. SoH is defined as the ratio of current capacity of the battery to its capacity at the beginning of life (BOL), whereas the battery RUL is considered as the life of the battery left to reach its end of life (EOL). In applications like EVs, battery's capacity is often considered as a parameter for Battery aging whereas in HEVs, the change in the internal resistance is usually measured as a SOH metric [7]. The EOL of a battery is considered when its capacity reduces to (70-80 %) of its initial value at the BOL or when the internal resistance doubles [5].

The energy consumption in a conventional fuel automobile is calculated by the amount of fuel consumed per unit distance, such as liters per kilometers (L/Km). On the other hand, for an EV, the energy consumption is the integration of the power output at the battery terminals. In other words, it is how much power was consumed per unit distance [8]. A model for energy consumption in EV is developed by [8] based on elevation changes, friction / regenerative braking, road travel cost -length, road travel cost -speed limit, ambient temperatures, auxiliary loads, and traffic information. The research gaps identified are driving style adaptation and more driver-specific related energy consumption features. Chang et al.. [9] had chosen SoC, SoH, battery pack current, battery pack voltage, altitude, motor temperature, motor Current, motor voltage and motor current as factors in developing the model for energy consumption. The research gaps identified were that the model has several assumptions like motor efficiency is constant over the entire operating range, the maximum motor current is constrained by the inverter setting, which limits the maximum motor torque. Such constraints limit the model accuracy in the case of real time simulation and analysis.

Accurate state of charge (SoC) estimate is essential for safe and reliable operation of lithium-ion battery in EV.

Precise estimation of SoC can prevent batteries from malfunctioning and reduce the possibilities of their overcharging and under charging, which may lead to permanent damage of batteries [11]. There are

several methods and technologies used for SoC estimation in electric vehicles like coulomb counting, voltage-based estimations, SoC estimation using open circuit voltage, model-based approaches, impedance spectroscopy, temperature based estimation, machine learning and AI, hybrid methods and smart battery management systems.

Zhang et al. [11] have done the estimation of SoC by considering an ideal battery model and comparing it with the actual battery under operation in an EV. This model is based on Kalman filtering and provides a near good estimate of SoC. The research gaps identified were that the model has emulated values of resistance and capacitance in the battery model which varies with time in the real-life system. Also, the parameters like temperature, SoC and aging levels are calculated by recursive least square method which is not good for long ranges and have poor extrapolation properties.

Zou et al. [11] considered a first order RC circuit model with nonlinear disturbance to depict the behavior of the battery. They compared different estimation methods with incorporating nonlinearities to the developed model. The research gaps identified is that inclusion of AI techniques may better the estimation of SoC when non linearities are considered.

Range estimation of an EV is an important area of development in EV market. One of the main hindrances in adaptation of EVs is range anxiety. The consumer requires the range of an EV compatible to conventional fuel automobiles. Using large capacity batteries seems to be an uneconomical and unsafe way of achieving larger range. Driving style is also an important factor and general tips for range optimization taught by the EV manufacturers are slow acceleration and deacceleration, use of regenerative braking, efficient use of climate control, following minimal route, keeping adequate tyre pressure, optimal charging and discharging and smaller wheel size (alloy wheels have larger diameter, hence increases the power requirement).

Estimation of energy consumption is the kernel of any range prediction technique. Cauwer et al. proposed using regression models depending on continuous aggregate data for range estimation in [13]. They represented the road topology by a digraph with edges and vertices, where the edges represent road section and vertices represent crossroads. Since a reasonable correlation with the real physical condition is difficult, these approaches have Modelling errors. Road network and traffic density are major contributors to estimation of range estimation but are neglected in most of the studies. Independent

variables which act as predictors for range estimation also depends on vehicle components.

Olivia et al. and Vaz et al. carried out the estimation by calculating the speed slope and the battery state of the EV in [14][15]. Estimation of driving pattern is based on previous data and usual driving practices which can't be adequately implemented for unknown routes and road conditions. Correlation between driving range and road network interconnections were not considered in these studies.

Conradi et al. considered it as NP-hard problem and used topological search in real time to investigate energy consumption of all the possible routes in the routing graph originating from the current position in [16]. The study lacks the details about the search technique used in computing the paths, estimation of energy consumption and correlation with road network.

Nunzio et al. considered the vehicle specific parameters, as well as the topology of the road network in which the vehicle operates and the real-time traffic conditions in [17]. The road network is converted into a directed adjoint graph which enables finding optimal energy consumption paths in the graph originating from the actual position of the vehicle and hence the driving range can be projected on a road map guiding an optimal path [18].

Energy Storage system modelling, comprising SoC estimation and range estimation has been done by many researchers but the research gaps like Multi Physics Modelling involving different physical processes, Cell Variability, Transient Behavior of battery, Aging and Degradation, Thermal Management, Fast Charging, Material Degradation, Electrode Heterogeneity, Safety Modelling, Scale up Effects, Experimental Validation, Data-driven Modelling, standardization of Modelling parameters and testing procedures, is essential to ensure consistency and comparability across different studies and applications.

Analytical Modelling of the model is used to predict future energy consumption based on road information. The energy consumption model includes five parts: the road load model, the powertrain loss model, the regenerative braking model, the auxiliary system model and the battery model.

3.0 Modelling of Energy Storage System for Electric Vehicle

The modelling of Energy storage system for EV's will be done based on the following attributes:

1. State of Charge (SoC) of the battery.

2. State of Health (SoH) of the battery.

3. Depth of Discharge (DoD) of the battery.

4. Ambient temperature.

5. Capacity fading/Aging of battery.

Modelling of energy storage system for EV significantly depends on the above-mentioned reasons. EV batteries operate efficiently in a specific temperature range. Battery manufacturers equip the Li-ion battery packs with required heating and cooling arrangement depending on the climatic conditions to ensure high SoH of energy storage system.

Batteries' performance degrades over time and usage due to power fading and capacity loss. This phenomenon is called battery aging, which occurs due to factors impacting battery performance, including chemistry degradation, manufacturing issues, atmospheric conditions (low/high temperature), and operational conditions. In fact, in EVs is important to know, the battery state of charge, power fade, capacity fade, and instantaneous available power, that are used by the battery management systems (BMS) to estimate the present operating condition of the battery packs. These components are usually functions of the state-of-charge (SOC), state of health (SOH) and temperature [19 - 22].

Main Goals of Modelling are as follows:

1. Performance Analysis: Assess range, acceleration, and efficiency.
2. Safety Evaluation: Ensure reliable operation under various conditions.
3. Lifetime Prediction: Estimate degradation and maintenance needs.
4. Cost Optimization: Balance performance and cost.

4.0 Controller Design

EV draws energy from a battery pack to fulfil the energy requirement of its motor drive and other electric systems. A battery pack comprises of number of cells connected in series. The cells of a battery pack encounter a condition of imbalance in voltage and charge among themselves after a few charge and discharge cycles. This is due to the slight characteristic change in material of each cell. This imbalanced cell condition result in overcharging and undercharging of the battery pack. It is hazardous for batteries in long run and may even lead to explosion of the battery pack. Thus, to improve the performance of the batteries, it is necessary to equalize the voltage and charge of all cells in a battery pack.

The battery charge equalization control system plays an important role to enhance the battery cell performance in terms of quality, efficiency and durability. A charge equalisation control system is therefore necessary for efficient and safe usage of batteries in EV's.

The design of Controller will be done to achieve the following attributes:

Equalisation of charge in battery cells.

2. Efficient charging rate of the battery.

3. Durability of battery pack.

5.0 PROBLEM STATEMENT

Based on the foregoing literature review it is evident that researchers focused to optimize energy consumption and efficiency of the EV. Improved designs of energy storage systems, better calculation of SoC and SoH developed in the last decade has improved accuracy of prediction of EV driving range and remaining life of the battery. Considering the recent trends and technology advancements in electric vehicles, following problem statement has been formulated:

"Optimization of Energy Consumption in electric vehicles using innovative approaches."

6.0 OBJECTIVES

Based on formulated problem statement an effort will be made to fill the identified research gaps by conducting comprehensive experimental study on the performance, modelling and validation of different aspects related to Electric Vehicles. The following objectives henceforth are proposed for pursuing this research work -

1. Estimation of SoC, DoD and remaining life of the battery.
2. Modelling and simulation of Energy Storage System for Electric Vehicle.
3. Optimal speed and energy consumption to achieve the best range of EV based on driver consciousness.
4. Design of Intelligent controller for optimal utilization of EV batteries.
5. Comparative Study of designed controller with existing Literature.

7.0 FLOW CHART

A flow chart is prepared to present the working order of the proposed study.

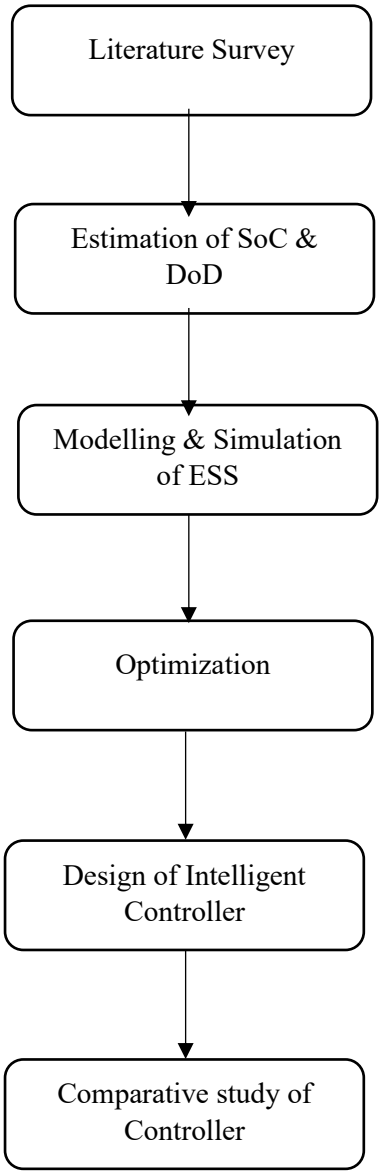

Figure 1 Flow Chart

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